

An Empirical Analysis of NMT-Derived Interlingual Embeddings and their Use in Parallel Sentence Identification

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Abstract

End-to-end neural machine translation has overtaken statistical machine translation in terms of translation quality for some language pairs, specially those with a large amount of parallel data available. Beside this palpable improvement, neural networks embrace several new properties. A single system can be trained to translate between many languages at almost no additional cost other than training time. Furthermore, internal representations learned by the network serve as a new semantic representation of words—or sentences—which, unlike standard word embeddings, are learned in an essentially bilingual or even multilingual context. In view of these properties, the contribution of the present work is two-fold. First, we systematically study the context vectors, i.e. output of the encoder, and their prowess as an interlingua representation of a sentence. Their quality and effectiveness are assessed by similarity measures across translations, semantically related, and semantically unrelated sentence pairs. Second, and as extrinsic evaluation of the first point, we identify parallel sentences in comparable corpora, obtaining an $F_1 = 98.2\%$ on data from a shared task when using only context vectors. F_1 reaches 98.9% when complementary similarity measures are used.

and Blunsom, 2013) as a promising alternative to statistical and rule-based systems. Nowadays, they are more than a promise. NMT systems are the state-of-the-art for language pairs with a large amount of parallel data (Bojar et al., 2016) and have nice properties that other paradigms lack. Just to point out three of them, being a deep learning architecture NMT does not require manually predefined features, it allows for the simultaneous training of systems across multiple languages, and it can provide zero-shot translations, i.e. translations for language pairs not directly seen in the training data (Ha et al., 2016; Johnson et al., 2016).

Multilingual neural machine translation systems (ML-NMT) have particularly interesting features. For performing multilingual translation, the network must project all the languages into the same common embedding space. In principle this space is multilingual, but the network is doing more than simply locating words according to their language and meaning independently. Previous analyses suggest that the network locates words according to their semantics, irrespective of their language (Sutskever et al., 2014; Ha et al., 2016; Johnson et al., 2016). That is somehow reinforced by the fact that zero-shot translation is possible (even if with low quality). If that is confirmed, ML-NMT systems are learning a representation akin to an interlingua for a source text and such interlingual embeddings could be used to assess cross-language similarity, among other applications.

In the past, the analysis of internal embeddings in NMT systems has been limited to visual studies; e.g., showing the proximity between semantically-similar representations. In the first part of this paper, we go beyond such graphical analyses and search for empir-

1 Introduction

End-to-end neural machine translation systems (NMT) emerged in 2013 (Kalchbrenner

ical evidence of the interlinguality. We address four specific research questions: (i) we investigate whether the embedding learned by the network for a source text also depends on the target language, (ii) how close representations of sentence pairs of a same language and across languages are, (iii) how distinguishable representations of semantically-similar and semantically-distant sentence pairs are, and (iv) how representations evolve throughout the training. These questions are addressed by means of statistics on cosine similarities between pairs of sentences both in a monolingual and a crosslingual setting. In order to do that, we perform a large number of experiments using parallel and comparable data in Arabic, English, French, German, and Spanish (*ar*, *en*, *fr*, *de*, and *es* from here onwards).

The second part of the paper is devoted to an application of the findings gathered in the first part. We explore the use of the “interlingua” representations to extract parallel sentences from comparable corpora. In this context, comparable corpora are text data on the same topic that are not direct translations of each other but that may contain fragments that are translation equivalents. Examples include Wikipedia or news articles on the same subject in different languages. We evaluate the performance of supervised classification algorithms based upon our best contextual representations when discriminating between parallel and non-parallel sentences in them.

The remaining of the article is organised as follows. Section 2 gives some background about NMT systems and describes related work. Section 3 describes the ML-NMT engines used in our analysis. Section 4 reports the study on the NMT-derived interlingual embeddings and discusses the results obtained. Section 5 presents a use case where we use the embeddings for identifying parallel sentences. The conclusions are drawn in Section 6.

2 Background

State-of-the-art NMT systems utilise a two-stage encoder-decoder architecture with recurrent neural networks (RNN) (Cho et al., 2014; Sutskever et al., 2014; Bahdanau et al., 2014). The purpose of the encoder is to project source

sentences into an embedding space. The purpose of the decoder is to generate target sentences from the encoder embeddings.

Let $s = (x_1, \dots, x_n)$ be a source sentence of length n . The encoder encodes s as a set of context vectors¹, one per word:

$$\mathbf{c} = \{\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_n\}. \quad (1)$$

Each component of this vector is obtained by concatenating the forward ($\vec{\mathbf{h}}_i$) and backward ($\overleftarrow{\mathbf{h}}_i$) encoder RNN hidden states:

$$\mathbf{h}_i = [\overleftarrow{\mathbf{h}}_i, \vec{\mathbf{h}}_i] \quad (2)$$

$$= [f(\overleftarrow{\mathbf{h}}_{i-1}, \mathbf{r}), f(\vec{\mathbf{h}}_{i+1}, \mathbf{r})], \quad (3)$$

where f is a recurrent unit (Gated Recurrent Units (GRU) (Cho et al., 2014) in our experiments) and \mathbf{r} is a representation of the source sentence given by the product of the word embeddings matrix and the one-hot vector representation of x_i : $\mathbf{r} = \mathbf{W}_x \cdot \mathbf{x}_i$.

The decoder generates the output sentence (y_1, \dots, y_m) of length m on a word-by-word basis. The recurrent hidden state of the decoder \mathbf{z}_j is computed using its previous hidden state \mathbf{z}_{j-1} , as well as the previous continuous representation of the target word \mathbf{t}_{j-1} and the weighted context vector \mathbf{q}_j at time step j :

$$\mathbf{z}_j = g(\mathbf{z}_{j-1}, \mathbf{t}_{j-1}, \mathbf{q}_j) \quad (4)$$

$$\mathbf{t}_{j-1} = \mathbf{W}_y \cdot \mathbf{y}_{j-1}, \quad (5)$$

where g is the recurrent unit of the decoder and \mathbf{W}_y is the matrix of the target embeddings. The weighted context vector \mathbf{q}_j is calculated by the attention mechanism as described in Bahdanau et al. (2014). Its function is to assign weights to the context vectors in order to selectively focus on different source words at different time steps of the translation. To this end, a single-hidden-layer feedforward neural network is utilised that assigns relevance scores (a , as they can be interpreted as alignment scores) to the context vectors, which are then normalised into probabilities by the softmax

¹Called “annotation vectors” by Bahdanau et al. (2014), who use “context vectors” to designate the vectors after the attention mechanism.

function:

$$a(\mathbf{z}_{j-1}, \mathbf{h}_i) = \mathbf{v}_a \cdot \tanh(\mathbf{W}_a \cdot \mathbf{z}_{j-1} + \mathbf{U}_a \cdot \mathbf{h}_i)$$

$$\alpha_{ij} = \frac{\exp(a(\mathbf{z}_{j-1}, \mathbf{h}_i))}{\sum_k \exp(a(\mathbf{z}_{j-1}, \mathbf{h}_k))}, \quad \mathbf{q}_j = \sum_i \alpha_{ij} \mathbf{h}_i$$

The attention mechanism takes the decoder’s previous hidden state \mathbf{z}_{j-1} and the context vector \mathbf{h}_i as inputs and weighs them up with the trainable weight matrices \mathbf{W}_a and \mathbf{U}_a , respectively.

A number of papers extend this architecture to deal with multilingual translation by using multiple encoders and/or decoders either with multiple or shared attention mechanisms (Luong et al., 2015; Dong et al., 2015; Firat et al., 2016; Zoph and Knight, 2016; Lee et al., 2016). A simpler approximation (Ha et al., 2016; Johnson et al., 2016) considers exactly the same architecture as the one-to-one NMT for many-to-many NMT using multilingual data with some additional labelling. Johnson et al. (2016) append the tag of the target language to the source-side sentences, forcing the decoder to translate to the appropriate language. Ha et al. (2016) also include tags specifying the language of every source word. Both papers show how these ML-NMT architectures can improve translation quality between under-resourced language pairs and how they can even be used for zero-shot translation. Given the premise that the encoder of an NMT system projects sentences into an embedding space, we can expect the encoder of ML-NMT systems to project sentences in different languages into a common (interlingual) embedding space. One of our aims is to study the characteristics of the internal representations of the encoder module in a ML-NMT system, and validate this assumption (see Section 4).

There is some relevant previous research on qualitative studies of NMT embedding space. Sutskever et al. (2014) show how a monolingual NMT encoder represents sentences with similar meaning close in embedding space. They show graphically —with two instance sentences— that clustering by meaning goes beyond a bag-of-words understanding, and that differences caused by the order of words are reflected in the representation. Ha et al.

(2016) go a step further and visualise the internal space in a many-to-one language NMT system. A 2D-representation of some multilingual word embeddings from the encoder after training displays translations and related words close together. Finally, Johnson et al. (2016) provide a visual evidence for a shared space for the attention vectors in an ML-NMT setup. Sentences with the same meaning but in different languages group together, except in the case of zero-shot translations. When a language pair has not been seen during training, the embeddings lie in a different region of the space. Notice that in the latter case (Johnson et al., 2016) the authors study the representation generated by the attention vectors, that is, the vectors showing the activations in the layer between encoder and decoder. The activations indicate which part of the source sentence is important during decoding to produce a particular chunk of the translation. Although the attention mechanism is shared across all the languages, the relevant chunks in the source sentence can vary depending on the target language.

In contrast to previous relevant research, in our work here we focus on the context vectors: the concatenation of the hidden states from the forward and the backward network in the encoding module —right before applying the attention mechanism. Our goal goes beyond understanding the internal representations that the network learns. We aim at finding an appropriate representation to assess multilingual similarity. With this objective in mind, we are looking for a representation that is as target-independent as possible. Similarity assessment is at the core of many natural language processing and information retrieval tasks. Paraphrase identification, which has been also applied to machine translation (Shimohata, 2004), is essentially similarity assessment, and so is the task of plagiarism detection (Potthast et al., 2010). In multi-document summarisation (Goldstein et al., 2000) finding two highly-similar pieces of information from two texts may imply it is worth adding it into a good summary. In information retrieval, and in particular in question answering (Hirschman and Gaizauskas, 2001), a high similarity between a document and an

Table 1: Description of the multilingual NMT systems used in the analysis. In all cases we use a learning rate of 0.0001, Adadelta optimisation, BPE vocabulary size of 2K, 512-dimensional word embeddings, mini-batch size of 80, and no drop-out.

	Languages	Factor	HiddenUnits	Vocab.	Training Corpora (# parallel sentences)
S1-w	{ <i>ar, en, es</i> }	word	1024	60K	{ <i>ar-en, en-ar, ar-es, es-ar</i>
S1-l	{ <i>ar, en, es</i> }	lemma	1024	60K	{($\sim 10M$) <i>en-es, es-en</i> ($\sim 13M$)
S2-w-d512	{ <i>de, en, es, fr</i> }	word	512	80K	<i>de-en, en-de</i> ($\sim 15M^*$), <i>en-es</i> ,
S2-w-d1024	{ <i>de, en, es, fr</i> }	word	1024	80K	{ <i>es-en</i> ($\sim 14M$), <i>es-fr, fr-es</i> ($\sim 15M$)
S2-w-d2048	{ <i>de, en, es, fr</i> }	word	2048	80K	<i>en-fr, fr-en</i> ($\sim 16M$)

* This value is obtained by oversampling

information request is a key factor of relevance. As expected, similarity estimation also plays an important role in machine translation. It is essential in MT evaluation and, in the current cross-language setting, to identify parallel corpora to feed a (neural) machine translation model with (Munteanu and Marcu, 2005). Efforts have been carried out to approach cross-language versions of these tasks without translating all the texts into one common language (e.g., (Bouma et al., 2008; Muñoz Terol et al., 2008; Potthast et al., 2011)), but using interlingua or multilingual representations instead. Still, such representations are usually hard to design and this is precisely when our neural context vector NMT embedding representation comes into play. A multilingual encoder offers an environment where interlingua representations are learnt in a multilingual context. To some extent, it can be thought as a generalisation of methods that project monolingual embeddings in two different languages into a common space to obtain bilingual word embeddings (Mikolov et al., 2013; Faruqui and Dyer, 2014; Madhyastha and España-Bonet, 2016).

Large amounts of parallel corpora are needed for training high-performance NMT systems and these are not always readily available. Since the NMT embeddings are learnt in a translation task, it seems natural to use them not only to generate translations but also to detect them in the first place, and in particular in comparable (rather than parallel) corpora. For low-resourced language pairs parallel data are scarce and, even for well-resourced language pairs, data on specific domains are often hard to obtain. Automatically extracting parallel corpora is then an important issue and a necessary step in many data settings.

3 NMT Systems Description

We carry out our experiments with two multilingual many-to-many NMT systems trained with Nematus (Sennrich et al., 2017). As done in Johnson et al. (2016) and similarly to Ha et al. (2016), our systems are trained on parallel corpora for several language pairs simultaneously, with the only addition of a tag in the source sentence to account for the target language “<2L2>” (e.g., <2ar> when the target language is Arabic). Table 1 summarises the key parameters of the engines.

Since our aim is to study the capability of NMT representations to characterise similar sentences within and across languages, we selected languages for which text similarity test sets and/or translation test sets are available. First we build a ML-NMT engine for *ar*, *en*, and *es*. We trained the multilingual system for the 6 language pair directions on 56 *M* parallel sentences in total with less than 50 tokens ($\sim 10 M$ parallel sentences per language pair). We used 1024 hidden units, which correspond to 2048-dimensional context vectors. The parallel corpus includes data from United Nations (Rafalovitch and Dale, 2009), Common Crawl², News Commentary³ and IWSLT⁴. We train system S1-w after cleaning and tokenising the texts. We used MADAMIRA (Pasha et al., 2014) for Arabic and the Moses tokeniser for the other languages. A second system called S1-l is trained on lemmatised sentences using the MADAMIRA lemmatiser for Arabic, and the IXA pipeline (Agerri et al., 2014) for

²<http://commoncrawl.org>

³<http://www.casmacat.eu/corpus/news-commentary.html>

⁴<https://sites.google.com/site/iwslt-evaluation2016/mt-track>

English and Spanish. In both cases we employ a vocabulary of 60 K tokens plus 2 K for subword units, segmented using Byte Pair Encoding (BPE) (Sennrich et al., 2016). For validation, we use sentences shorter than 50 tokens from different corpora (1500 sentences in *es-en* from newstest2012⁵, 1000 sentences in *ar-en* from eTIRR Arabic English News Text⁶, and a 1000 sentences partition in *ar-es* from News Commentary).

We build a second ML-NMT engine for *de*, *fr*, *en*, and *es*. We train the system with data on 4 language pairs: *de-en*, *fr-en*, *es-en* and *es-fr*. Although some corpora exist for the remaining two (*es-de* and *fr-de*), we exclude them to study these pairs as instances of zero-shot translation. The parallel corpus includes data from United Nations (Chen and Eisele, 2012), Common Crawl, Europarl (Koehn, 2005), EMEA (Tiedemann, 2009) and Scielo⁷. We obtain about 15 M parallel sentences per language pair —notice that for *de-en*, we needed oversampling in order to reach the same amount of data and we triple the original sentences. The 22 K sentences shorter than 50 tokens in the newstest2012 for the 4 main language pairs are used for validation purposes. For this engine, we use a larger vocabulary size, 80 K type tokens plus 2 K for BPE, given that, compared to our first set of experiments, one language more is involved. Regarding the number of hidden units, we experiment with three configurations: S2-w-d512, S2-w-d1024, and S2-w-d2048.

3.1 Test Sets and Evaluation

In order to assess the degree of similarity between sentences, we consider three types of test sets. The source side is always the same and it is aligned to a target set that contains either: (i) exact translations of the source, (ii) highly-similar sentences (both mono- and cross-language), and (iii) unrelated sentences (both mono- and cross-language). For Arabic, English and Spanish, we build the three kinds of pairs out of the recently-held “Semantic Textual Similarity Task at SemEval

2017” (Agirre et al., 2017 (to appear)⁸). The task asks to assess the similarity between two texts within the range $[0, 5]$, where 5 stands for semantic equivalence. We extract the subset of sentences with the highest similarity, 4 and 5, and use 140 sentences originally derived from the Microsoft Research Paraphrase Corpus (Dolan and Brockett, 2005) (MSR), and 203 sentences from WMT2008⁹ to build our final test set with 343 sentences (subSTS2017). These data were available for *ar* and *en* but not for *es*, so we manually translated the MSR part of the corpus into *es*, and gathered the Spanish counterparts of the WMT2008 from the official set. With this process, we generated the test with translations (trad) and high-similarity sentence pairs (semrel). We shuffled one of the sides of the test set to generate the unrelated pairs (unrel).

In order to simultaneously evaluate the German, French, English and Spanish experiments, we used the test set from WMT2013 (newstest2013); the last edition that includes these four languages. The test set contains 3000 sentences translated into the four languages. As before, we shuffle one of the sides to obtain the test set with unrelated sentence pairs, but we could not generate the equivalent set with high-similarity pairs.

4 Context Vectors in Multilingual NMT Systems

The NMT architecture used for the experiments is the encoder-decoder model with recurrent neural networks and attention mechanism described in Section 2, as implemented in Nematus.

We use the sum of the context vector associated to every word (Eq. 1) at a specific point of the training as the representation of a source sentence s :

$$\mathbf{C} = \sum_{i=1}^n c_i. \quad (6)$$

This representation depends on the length of the sentence. However, we stick to this definition rather than using a mean over words because the length of the sentences is an indica-

⁵<http://www.statmt.org/wmt14/translation-task.html>

⁶LDC2004E72 available from the Linguistic Data Consortium

⁷<http://www.scielo.org>

⁸<http://alt.qcri.org/semeval2017/task1>

⁹<http://www.statmt.org/wmt08/shared-evaluation-task.html>

tor of their similarity. That is, sentences with similar meaning tend to have similar lengths.¹⁰

Given a sentence s_1 represented by \mathbf{C}_{s_1} and a sentence s_2 represented by \mathbf{C}_{s_2} , we can estimate their similarity by means of the cosine measure:

$$\text{sim}(\mathbf{C}_{s_1}, \mathbf{C}_{s_2}) = \frac{\mathbf{C}_{s_1} \cdot \mathbf{C}_{s_2}}{\|\mathbf{C}_{s_1}\| \|\mathbf{C}_{s_2}\|}. \quad (7)$$

4.1 Graphical Analysis

Context vectors are high-dimensional structures: for the standard 1024-dimensional hidden layers one has 2048-dimensional context vectors. In order to get a first impression on the behaviour of the embeddings, we project the vectors for a set of sentences into a 2D space using t-Distributed Stochastic Neighbour Embedding (t-SNE) (Van Der Maaten, 2014).

We consider 21 sentences extracted from the trial set of the Semantic Textual Similarity Task at SemEval 2017 for this purpose. Figure 1 shows the set of sentences and the relations between triplets. Sentences are divided into 7 triplets with 3 sentences each. Each sentence is an exact translation in *ar*, *en* and *es*. Some triplets are related semantically. For instance, a triplet with the element “Mandela’s condition has improved” is semantically related to the triplet with the element “Mandela’s condition has worsened over past 48 hours”. In a real multilingual space, one would expect sentences within a triplet to lie together and sentences within related triplets to be close but, as Figure 2 shows, the range of behaviours may be diverse. The plot shows the evolution of the context vectors for these 21 sentences throughout the training (central panel), paying special attention to an early (left panel) and a late stage (right panel).

At the beginning of the training, English and Spanish sentences in a same triplet (same colour) lie close together and, for some triplets, they even overlap; see $t4$ and $t7$. This is an effect of having a representation that depends on the length of the sentence: the elements in $t4$ and $t7$ not only share some vocabulary but also have very similar lengths. Arabic sentences remain together, almost irrespective of their

meaning. One has to take into account that *en* and *es* are closer between them than to *ar* — they share a subject-verb-object structure and have many cognates. Meanwhile, *ar* is closer to *es* than to *en* — Arabic influenced the Spanish language during 800 years. At this early stage in training, the closer languages have already been unified (*en* and *es*) and sentences can be grouped according to their semantics, but the most distant language (*ar*) is not in the same stage yet. For Arabic sentences, the language is more important than the semantics: sentence $s9$ is closer to $s14$ (another sentence in Arabic with similar length) than to $s7$ (a strict and longer translation of $s9$ into Spanish).

As training continues, Arabic sentences spread through the space and slowly tend to join their counterparts in the other languages. English and Spanish sentences also move apart towards a more general interlingua position. That is, there is a flow from near to overlapping locations for translations of the same sentence towards locations grouped by topic, irrespective of the language (look at the evolution of the related triplets $t6$ and $t7$ for example). This evolution must be considered if one wants to use context vectors as a semantic representation of a sentence: representations at different points of the training process might be useful for different tasks.

The expected behaviour, however, is not observed for all the triplets. It is the case for $t1$ or $t5$, where representations of the individual sentences get closer at every iteration. Still, it is not the case for other triplets, such as $t6$, in which sentences are farther away from each other at each iteration (notice that this triplet has the longest sentences and the highest length variation).

A more systematic study is necessary in order to be able to draw strong conclusions. In the following sections we conduct such a study and draw conclusions quantitatively, rather than only qualitatively. We also determine at which point in the training process the internal representation of a sentence is optimal for our aim: parallel sentence selection from comparable data.

¹⁰We explored alternative combinations and this one resulted in the best performance.

s1:t1	Spain princess testifies in historic fraud probe
s2:t1	Princesa de España testifica en juicio histórico de fraude
s3:t1	أميرة أسبانيا تدلي بشهادتها في قضية احتيال تاريخي.
s4:t2	You do not need to worry.
s5:t3	You don't have to worry.
s6:t2	No necesitas preocuparte.
s7:t3	No te tienes por que preocupar.
s8:t2	لا ينبغي أن تقلق
s9:t3	لا ينبغي أن تجزع.
s10:t4	Mandela's condition has 'improved'
s11:t5	Mandela's condition has 'worsened over past 48 hours'
s12:t4	La salud de Mandela ha 'mejorado'
s13:t5	La salud de Mandela 'ha empeorado en las últimas 48 horas'
s14:t4	لقد تحسّنت حالة مانديلا الصحية.
s15:t5	سَاءت الحالة الصحية لمانديلا خلال ال ٤٨ ساعة الماضية.
s16:t6	Vector space representation results in the loss of the order which the terms are in the document.
s17:t7	If a term occurs in the document, the value will be non-zero in the vector.
s18:t6	La representación en el espacio de vectores implica la pérdida del orden en el que los términos ocurren en el documento.
s19:t7	Si un término ocurre en el document, el valor en el vector será distinto de cero.
s20:t6	يؤدي تمثيلُ فضاءِ المتجهِ إلى فقد الترتيب الذي تكون عليه المصطلحات في الوثيقة.
s21:t7	إذا ما ورد مصطلح في الوثيقة، فالقيمة ستكون غيرصفريّة المتجه.

Figure 1: Set of 21 sentences chosen for the graphical analysis. The number of sentence s and triple t used in subsequent plots is shown on the left-hand side. Sentences within a triplet have the exact same meaning (they are literal translations in $\{ar, en, es\}$). Triplets $(t2, t3)$, $(t4, t5)$ and $(t6, t7)$ share the topic, and therefore are close semantically.

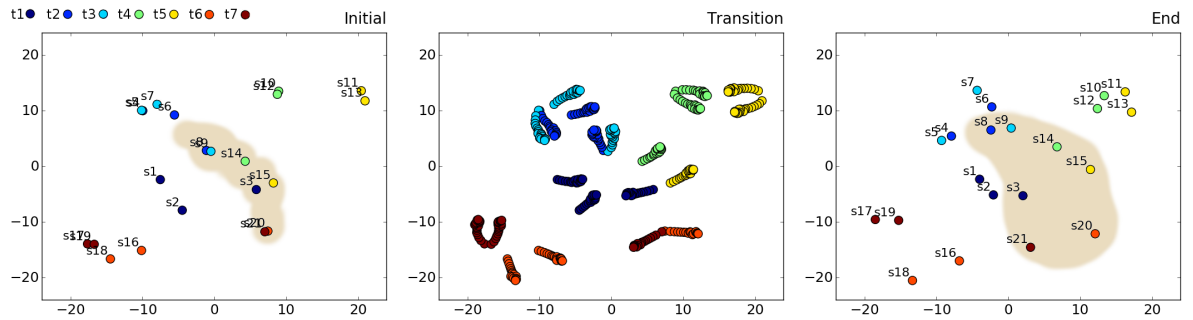


Figure 2: 2D t-SNE representation of the context vectors of the 21 sentences selected in Figure 1 obtained with the multilingual $\{ar, en, es\}$ NMT system, S1-w. The left-most plot shows the vectors quite at the beginning of the training (after $10 \cdot 10^6$ sentences) and the right-most plot shows the vectors after 1.5 epochs ($178 \cdot 10^6$ sentences). The evolution during training is plotted in the middle panel. Shaded regions include only Arabic sentences.

4.2 Source vs. Source-Target Semantic Representations

The training of the ML-NMT systems involves one-to-many instances, that is, for the same source language L1 one has different examples of translations into L2, L3 or L4. A first question one can address given this set up is whether the interpretation of a source sentence learnt by the network depends on the language it is going to be translated into or not. In a truly interlingual space, such a representation should be the same, or at least very close.

In order to test this, we computed the cosine similarity between the representation of a source sentence s when it is translated with the same engine into two different languages L_i and L_j :

$$\langle 2L_i - 2L_j \rangle \equiv \text{sim}(s_{\langle 2L_i \rangle}, s_{\langle 2L_j \rangle}) \quad (8)$$

Sentence representations are extracted with engine S1-w for $\{ar, en, es\}$ on subSTS2017 data and with engine S2-w-d1024 for $\{de, en, es, fr\}$ on newstest2013. Afterwards, we compute the mean over all the sentences in a test set. Table 2 shows the results for this analysis.

Similarities are close to one in all cases; a number that would indicate that representations are fully equivalent, and are compatible with one within a 2σ interval. Although differences among languages and test sets are not statistically significant at that level, some general trends can be observed. Despite the fact that the similarity between instances of the same sentence is not one, it is larger than the similarity between closely related sentences when translated into the same language (see Section 4.3). That is, we can identify a sentence by a unique representation. Also notice that there is no difference either when we translate into a language without any direct parallel data (zero-shot translation): for $es-de$ and $fr-de$, system S2-w-d1024 had no data, but the similarities involving these pairs (marked with an asterisk in Table 2) are not statistically-significantly different to those involving $es-fr$ and $es-en$, for example.

Finally, we can strengthen the correlation between the relatedness between languages and the closeness of the internal representations observed also via the first graphical analysis. The representation of an Arabic sentence

Table 2: Cosine similarities between the internal representations of the sentences in subSTS2017 (with system S1-w) and newstest2013 (S2-w-d1024) when translated from L1 into different languages L2, L3, L4. 1σ uncertainties are shown in parentheses and affect the last significant digit; similarities when a zero-shot language pair is involved are marked with an asterisk.

	L1 {L2, L3, L4}	$\langle 2L_2-2L_3 \rangle$	$\langle 2L_2-2L_4 \rangle$	$\langle 2L_3-2L_4 \rangle$
<i>ar</i>	$\{en, es, \phi\}$	0.97(5)	–	–
<i>en</i>	$\{es, ar, \phi\}$	0.94(5)	–	–
<i>es</i>	$\{ar, en, \phi\}$	0.91(5)	–	–
<i>de</i>	$\{fr, en, es\}$	*0.97(2)	*0.98(2)	*0.96(2)
<i>fr</i>	$\{en, es, de\}$	0.96(2)	*0.96(2)	*0.97(2)
<i>en</i>	$\{es, de, fr\}$	0.96(2)	0.98(2)	0.96(2)
<i>es</i>	$\{de, fr, es\}$	*0.97(2)	*0.96(2)	0.97(2)

when translated into *en* or *es* is almost the same ($\text{sim} = 0.97 \pm 0.05$), but the difference in the representation of a Spanish sentence when translated into *ar* or *en* is the largest one ($\text{sim} = 0.91 \pm 0.05$) due to the disparity between *ar* and *en*. The same effect, but at a lower degree, is observed in the $\{de, fr, en, es\}$ case when making the distinction between $\{fr, es\}$ and $\{de, en\}$ as two groups of “close” languages.

4.3 Representations throughout Training

During training, the network learns the most appropriate representation of words/sentences in order to be translated, so the embeddings themselves evolve over time. As we have seen with the graphical analysis (Section 4.1), it is interesting to follow this evolution and examine how sentences are grouped together depending on their language and semantics. For this, we analyse in parallel an engine trained on lemmatised sentences (S1-l) and one trained on tokenised sentences (S1-w). The rationale behind this is that the vocabulary in the lemmatised system is smaller and therefore can be better covered during training. Still, the ambiguity becomes higher, which could damage the quality of the representations.

Table 3 shows the results. At the beginning of the training process, after having seen $4 \cdot 10^6$ sentences only, the results are still very much dependent on the language. Exact trans-

Table 3: Cosine similarities between the obtained representations of the sentences in the sub-STS2017 test set with the two configurations of the $\{ar, en, es\}$ system, S1-w and S1-l. Results are shown for the available language pairs, both monolingual and cross-language, and for the three versions of the set with translations (*trad*), semantically similar sentences (*semrel*) and unrelated sentences (*unrel*). Notice that a *trad* set cannot be built in the monolingual case. Δ_{tr-ur} is the difference between the mean similarity seen in translations and in unrelated sentences. 1σ uncertainties are shown in parentheses and affect the last significant digits.

0.1 EPOCHS ($\sim 4 \cdot 10^6$ sentences)										
	S1-words					S1-lemmas				
	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>
<i>trad</i>	–	–	0.26(10)	0.76(05)	0.40(09)	–	–	0.44(07)	0.81(04)	0.53(05)
<i>semrel</i>	0.92(03)	0.93(01)	0.24(10)	0.75(06)	0.38(09)	0.93(01)	0.94(01)	0.42(07)	0.80(05)	0.51(06)
<i>unrel</i>	0.65(13)	0.66(13)	0.06(09)	0.53(11)	0.14(10)	0.70(09)	0.73(09)	0.27(09)	0.63(10)	0.33(08)
Δ_{tr-ur}	–	–	0.20(13)	0.23(12)	0.26(13)	–	–	0.16(11)	0.18(11)	0.20(10)

0.5 EPOCHS ($\sim 28 \cdot 10^6$ sentences)										
	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>
<i>trad</i>	–	–	0.61(07)	0.67(06)	0.76(06)	–	–	0.51(06)	0.68(05)	0.60(06)
<i>semrel</i>	0.86(07)	0.87(06)	0.58(08)	0.65(07)	0.73(07)	0.84(08)	0.86(06)	0.47(07)	0.66(07)	0.57(07)
<i>unrel</i>	0.48(12)	0.43(12)	0.30(10)	0.37(11)	0.37(11)	0.45(12)	0.46(11)	0.23(08)	0.39(10)	0.27(09)
Δ_{tr-ur}	–	–	0.32(12)	0.30(12)	0.39(12)	–	–	0.28(11)	0.29(11)	0.33(11)

1.0 EPOCH ($\sim 56 \cdot 10^6$ sentences)										
	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>
<i>trad</i>	–	–	0.61(08)	0.65(07)	0.74(06)	–	–	0.51(06)	0.63(06)	0.60(06)
<i>semrel</i>	0.83(09)	0.85(07)	0.57(08)	0.63(08)	0.70(08)	0.81(10)	0.83(07)	0.47(07)	0.61(08)	0.56(07)
<i>unrel</i>	0.41(12)	0.37(11)	0.27(10)	0.32(11)	0.31(10)	0.38(12)	0.40(11)	0.21(08)	0.33(09)	0.25(09)
Δ_{tr-ur}	–	–	0.34(12)	0.33(13)	0.43(12)	–	–	0.28(11)	0.29(11)	0.33(11)

2.0 EPOCHS ($\sim 112 \cdot 10^6$ sentences)										
	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>	<i>ar</i>	<i>en</i>	<i>ar-en</i>	<i>ar-es</i>	<i>en-es</i>
<i>trad</i>	–	–	0.59(07)	0.62(07)	0.71(07)	–	–	0.50(06)	0.60(06)	0.59(07)
<i>semrel</i>	0.80(10)	0.83(08)	0.54(08)	0.60(08)	0.67(08)	0.78(11)	0.82(08)	0.46(07)	0.58(08)	0.56(08)
<i>unrel</i>	0.37(12)	0.34(11)	0.26(09)	0.30(10)	0.29(10)	0.33(11)	0.36(10)	0.21(08)	0.29(08)	0.22(08)
Δ_{tr-ur}	–	–	0.33(12)	0.32(12)	0.42(12)	–	–	0.29(10)	0.31(10)	0.37(11)

lations in *ar-es* have a similarity of 0.81 ± 0.04 , whereas exact translations in *ar-en* have a similarity of 0.44 ± 0.07 (see the first row for system S1-lemmas). Perhaps for this reason monolingual pairs show higher similarity values than cross-language pairs, even for unrelated sentences ($sim = 0.70 \pm 0.09$ for *ar* and $sim = 0.73 \pm 0.09$ for *en*). Nevertheless, within a language pair the system has already learned the meaning of the sentences: cosine similarities are the highest for exact translations (*trad*), slightly lower for semantically related sentences (*semrel*) and significantly lower for unrelated sentences (*unrel*). The difference between the mean similarities

obtained for translations and unrelated sentences,

$$\Delta_{tr-ur} \equiv \Delta(sim(trad) - sim(unrel)),$$

shows how, already at this point, parallel sentences can be identified and located in the multilingual space, even though the similarity for translations is in general far from one and the similarity for unrelated sentences is far from zero.

At this starting point, sentences lie closer together irrespective of their meaning in the lemmatised system than in the tokenised one. Similarities are always higher for S1-l than for

Table 4: Similar to Table 3 for the $\{de, fr, en, es\}$ engine on the newstest2013 test sets after half an epoch. In this case, three system configurations are shown that vary the size of the last hidden layer of the encoder: S2-w-d512, S2-w-d1024 and S2-w-d2048.

	<i>de-en</i>	<i>de-es</i>	<i>de-fr</i>	<i>en-es</i>	<i>en-fr</i>	<i>es-fr</i>
S2-w-d512						
<i>trad</i>	0.61(10)	0.62(10)	0.62(10)	0.66(10)	0.66(10)	0.73(10)
<i>unrel</i>	0.25(10)	0.27(10)	0.27(10)	0.26(10)	0.26(10)	0.30(11)
Δ_{tr-ur}	0.36(14)	0.35(14)	0.35(14)	0.40(14)	0.41(14)	0.43(15)
S2-w-d1024						
<i>trad</i>	0.62(10)	0.62(10)	0.62(10)	0.66(10)	0.66(10)	0.73(10)
<i>unrel</i>	0.26(10)	0.27(10)	0.27(10)	0.26(10)	0.27(10)	0.31(11)
Δ_{tr-ur}	0.36(14)	0.35(14)	0.34(14)	0.39(14)	0.40(14)	0.42(15)
S2-w-d2048						
<i>trad</i>	0.59(10)	0.58(10)	0.58(10)	0.61(10)	0.62(10)	0.69(11)
<i>unrel</i>	0.24(09)	0.25(09)	0.25(09)	0.23(09)	0.23(09)	0.27(10)
Δ_{tr-ur}	0.35(13)	0.33(14)	0.33(14)	0.38(13)	0.39(14)	0.42(15)

its counterpart in S1-w. The separation between translations and unrelated sentences is always more important in the S1-w (Δ_{tr-ur} is higher). This is true all along the training process, confirming that the ambiguity introduced by the lemmatisation damages the representativity of the embeddings.

When the training process has covered $28 \cdot 10^6$ sentences, half an epoch for this system, the difference among languages has diminished. Now sentences lie closer together in the tokenised system than in the lemmatised one, irrespective of their meaning. From this point onwards, this trait is maintained. Although all similarities keep going down throughout the training, even for translations, Δ_{tr-ur} remains almost constant. The maximum value for this difference is found after one epoch ($\sim 56 \cdot 10^6$ sentences) for all the cross-language pairs in the tokenised system. In this case, Δ_{tr-ur} is 0.34 ± 0.12 for *ar-en*, 0.33 ± 0.13 for *ar-es* and 0.43 ± 0.12 for *en-es*. Again, the distinction is the clearest for the closest language pair and diminishes when Arabic is involved, mainly because translations involving Arabic are more difficult to detect (the mean similarity between *en-es* translations is 0.74 ± 0.06 ; 0.61 ± 0.08 for *ar-en*).

Analogous conclusions can be drawn from the $\{de, fr, en, es\}$ engine. Table 4 includes the results. The maximum distinction between related and unrelated sentences, Δ_{tr-ur} , is found after $\sim 56 \cdot 10^6$ sentences, half an

epoch in this case, even though the difference was well established at a third of an epoch. Δ_{tr-ur} is 0.3 ± 0.1 when German is involved (*de-en*, *de-es*, *de-fr*) and 0.4 ± 0.1 when it is not (*en-es*, *en-fr*, *es-fr*). The difference is mostly given by the similarity between translations, which is higher when German is not concerned.

Notice that this optimal point does not correspond to the optimal point regarding translation quality. Figure 3 displays the progression of the BLEU score along training for the English-to-Spanish translation. The dashed vertical line indicates the iteration where Δ_{tr-ur} is maximum. At this time, the engine is still learning, as seen by the fact that the translation quality is clearly increasing.

Another interesting observation is that the expressivity of the embeddings does not depend on their dimensionality. Context vectors with 1024 dimensions (S2-w-d512), 2048 dimensions (S2-w-d1024) and 4096 dimensions (S2-w-d2048), lead to similar figures for similarity values between pairs of sentences. At the beginning of the training, S2-w-d1024 gives slightly better representations than the other two systems, but this difference is narrowed when the training advances. The training time almost doubles when doubling the dimensionality of the hidden layer, but this higher capacity does not result in a better description of the data. Actually, 4096-dimensional vectors perform worse than the 1024-dimensional ones at

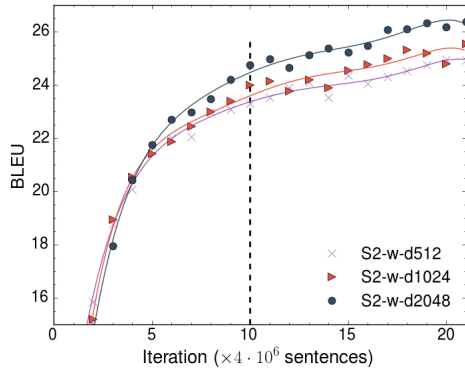


Figure 3: BLEU evolution throughout training on newstest2013 when translated from English into Spanish with three systems that differ in the size of the hidden layer (see text). The dotted vertical line marks the point where context vectors have a maximum descriptive power.

all the training stages. However, translation quality does depend on the size of the hidden layer and, in our experiments, S2-w-d2048 performs better than the lower-dimensional systems (see Figure 3 to observe the variation for the English-to-Spanish translation).

5 Use Case: Parallel Sentence Extraction

The previous section shows how ML-NMT context vectors can be used as a representation that allows to calculate sensitive similarities between sentences with the potential to distinguish translations from non-translations and even translations from pairs with similar meaning. As a first application, we can use these representations learned when mapping parallel sentences—the NMT system training—in order to detect new parallel pairs. In particular, we use a semantic similarity measure based on the context vectors obtained with the NMT system of Section 4 to extract parallel sentences and study its performance as compared to other measures.

Our translation engine is the ML-NMT system for *de*, *fr*, *en*, and *es*, described in Section 3. According to the conclusions gathered in Section 4, we use system S2-w-d512 after half an epoch of training for extracting the context vectors. This system gives us the best trade-off between speed (low-dimensional vectors are extracted faster) and dissociation between translations and unrelated sentences, as this is the training point where the difference

$\Delta_{\text{tr-ur}}$ is maximum.

5.1 Parallel Sentence Identification

In order to perform a complete analysis, we consider five additional/complementary measures to context vectors and test different scenarios. We borrow two well known representations from cross-language information retrieval to account for syntactic features by means of cosine similarities: (i) character n -grams (McNamee and Mayfield, 2004), considering $n = [2, 5]$ and (ii) pseudo-cognates. From a natural language point of view, cognates are “words that are similar across languages” (Manning and Schütze, 1999). We relax the concept of cognate and consider as pseudo-cognates any words in two languages that share prefixes. To do so, tokens shorter than four characters are discarded, unless they contain non-alphabetical characters. The resulting tokens are cut off to four characters (Simard et al., 1993). The necessary preprocessing consists of casefolding, punctuation marks removal, and diacritics removal only. For the character n -gram measure, we also remove spaces to better account for compounds in German. Besides, we include general features at sentence level such as (iii) token and (iv) character counts, and (v) the length factor measure (Pouliquen et al., 2003).

We test three different scenarios to observe the effect of context vectors when extracting sentence pairs and compare them against the other standard characterisations:

ctx: only context vectors are used,

comp: the set of five complementary measures is used,

all: a combination of *ctx* and *comp* is used.

For each of these scenarios, we learn a binary classifier on annotated data. We use the *de-en* and *fr-en* training corpora provided for the shared task on identifying parallel sentences in comparable corpora at the “10th Workshop on Building and Using Comparable Corpora”¹¹ (BUCC 2017). This set contains 1,454,890 sentences from Wikipedia

¹¹<https://comparable.limsi.fr/bucc2017/bucc2017-task.html>

Table 5: Precision (P), Recall (R) and F₁ scores (%) obtained on the binary classification of pseudo-alignments on the held-out test set.

		<i>de-en</i>			<i>fr-en</i>			joint		
		P	R	F ₁	P	R	F ₁	P	R	F ₁
<i>ctx</i>	Thrs.	95.5	97.1	96.3	95.4	100.0	97.7	98.3	98.1	98.2
	SVM	96.2	96.2	96.2	95.6	99.1	97.3	97.1	98.0	97.6
	GB	97.0	95.7	96.4	95.6	99.6	97.6	97.0	97.3	97.2
	Ens.	98.2	95.7	97.0	95.6	99.1	97.3	96.9	97.8	97.3
<i>comp</i>	SVM	72.3	85.5	78.4	76.7	85.1	80.7	73.4	80.9	77.0
	GB	93.5	85.1	89.1	97.2	93.2	95.1	96.9	90.7	93.7
	Ens.	84.0	89.4	86.6	95.5	95.5	95.5	93.4	91.6	92.5
<i>all</i>	SVM	74.6	86.4	80.1	81.8	87.3	84.5	86.1	85.6	85.8
	GB	98.7	96.6	97.6	99.1	99.6	99.3	98.9	98.9	98.9
	Ens.	99.1	96.6	97.8	99.1	99.6	99.3	98.7	99.1	98.9

and News Commentary from which approximately 20,000 are aligned sentence pairs. Negative indexes are manually added by randomly pairing up the same amount of non-matching pairs. From the full set, we use 35,000 instances for training and evaluating classifiers with 10-fold cross-validation, 4,000 instances for training an ensemble of the best classifiers and 1,000 instances for held-out testing purposes.

For *ctx*, where only the context vector similarities are considered, the problem can be reduced to finding a suitable decision threshold. To this end, similarity values between the lowest value among positive examples and the highest value among negative samples are incrementally increased by a step size of 0.005 and the threshold giving the highest accuracy on the training set is selected. With this methodology, we obtain a threshold $t = 0.43$ for *de-en* leading to an accuracy of 97.2%, and 0.41 for *fr-en* with an accuracy of 97.4%. These values are slightly lower than the ones reported in Table 4, but consistent with them. The thresholds in both cases depend on the language pair, but the fact that we are working with an interlingua representation makes the differences minimal. This allows us to estimate a joint threshold for the full training set in *de-en* and *fr-en* and later use this decision boundary for other language pairs. If we do the search on the joint datasets the best threshold is $t = 0.43$ leading to an accuracy of 97.2% in the training set.

In *comp* and *all* we have 7 and 8 features respectively, and we employ supervised classi-

fiers rather than a simple threshold estimation. We train support vector machines (SVM) using the radial basis function kernel and gradient boosting (GB) on the deviance objective function with 10-fold cross-validation. A soft voting ensemble (Ens.) of these two algorithms is trained in order to obtain the final model. In all these scenarios, we use the implementations of Python’s scikit-learn¹² package.

Table 5 shows Precision (P), Recall (R) and F₁ scores for the three scenarios. Notice that a simple greedy threshold search is better than any of the machine learning counterparts when only context vectors are used, but differences are not significant. The greedy search on the context vector similarities gives a better F₁ score on the held-out test set than an ensemble of SVM and GB operating only the set of additional features with almost no knowledge of semantics. As we have argued in the previous section, translations and non-translations are clearly differentiated by a cosine similarity of the context vectors for these pairs of languages, as the difference between the mean similarities of translations and unrelated texts is much higher than its uncertainty ($\Delta_{tr-ur} = 0.36 \pm 0.14$ for *de-en*, and 0.41 ± 0.14 for *fr-en*). This clear distinction in the similarities is translated into a F₁ = 98.2% in the task of parallel sentence identification.

Due to its interlingual nature, our feature behaves equally well in both language pairs and improves in the multilingual setting (joint columns in Table 5). On the contrary, the set

¹²<http://scikit-learn.org/stable/index.html>

of complementary features depends on the language pair and has a drop in performance for *de-en*. For this reason, the results in the multilingual setting are always worse than in the bilingual one. This fact is inherited in the *all* scenario, where the classification for the joint corpus has $F_1 = 98.9\%$, which is lower than the one obtained for *fr-en* alone ($F_1 = 99.3\%$). Nevertheless, semantic and syntactic similarity features are complementary and the combination of all similarity measures slightly improves precision, recall and F_1 in the multilingual setting. Finally, it is worth noting the high recall derived from the context vectors, which reaches 100% for *fr-en* and falls to 98.1% for the joint data, being still 6.5 points higher than for the *comp* features.

6 Conclusions

In this article we provide evidence of the interlingual nature of the context vectors generated by an end-to-end multilingual neural machine translation system and study their power in the assessment of monolingual and cross-language similarity.

We investigate how the representation of a sentence varies in order to be accommodated to a particular target language and observe that the difference is negligible, even though it grows when we consider distant target languages such Arabic and English. Even in these cases, the representation of a sentence is unique enough as closely related sentences have a smaller similarity than different instances of a same sentence.

Results also show that the contextual interlanguage vectors are able to differentiate among sentences with identical, similar, and different meaning across different languages — including Arabic, English, French, German, and Spanish. Our training-evolution experiments reveal that vectors at early training are the best ones for similarity assessment, whereas the optimal ones for translation require further training. Besides, whereas for reaching a good translation quality the dimensionality of the vectors is important, we show that the expressivity of the embeddings as regards semantic similarity within and across languages does not depend on their dimension.

As a direct application of our similarity fea-

ture, we identify parallel sentences in comparable corpora achieving a performance of $F_1 = 98.2\%$ on data of the shared task on identifying parallel sentences in comparable corpora at BUCC 2017. The fact that this is an interlingual feature allows to use data on different languages simultaneously for setting a threshold or a classification model that can be later used on other languages without a loss of performance.

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